MSDS 692 Data Science Practicum I: "Recipe for Success: Data-Driven Strategies for New Restaurant Owners in San Diego" by Tia Page

This project titled "Recipe for Success: Data-Driven Strategies for New Restaurant Owners in San Diego," aims to provide data-driven insights to help new and prospective restaurant owners succeed in San Diego's competitive market. The goals of this project are to identify key success factors for restaurants in San Diego, recommend optimal locations in the city to establish one's restaurant, and find strategies to enhance customer experience. All of these factors are essential in navigating the competitive nature of San Diego's food industry.

This project utilizes Python to analyze data from various sources, including restaurant reviews, demographic data, and geographic information. The code is organized into sections for data collection, cleaning, exploratory analysis, machine learning, and visualization to achieve these goals. By leveraging these techniques, this project empowers aspiring restaurant owners with the knowledge to thrive in San Diego's culinary landscape.

Data Collection

This project leverages a multi-faceted data collection approach to gather comprehensive information on San Diego restaurants and their surrounding market. The data collection process involved the following key steps:

- **San Diego Zip Codes and Neighborhoods:** A list of San Diego zip codes and their corresponding neighborhood names was retrieved using web scraping techniques from the website BkylnDesigns.com. This data provides the geographic foundation for the analysis, enabling the segmentation and comparison of restaurants across different neighborhoods.
- **Land Area Information:** Land area data for each San Diego zip code was obtained through web scraping from USA.com. This information allows for the calculation of population density, which can be a crucial factor in understanding restaurant performance and market saturation.
- **Demographic information** for each zip code, including population, number of households, median income, and average income, was collected from Point2Homes.com. Due to website restrictions, this data was manually compiled from an online table into an Excel spreadsheet. Demographic data provides insights into the socioeconomic characteristics of different neighborhoods, helping to understand customer profiles and potential market segments.
- **Restaurant Listings and Google Review URLs:** A list of restaurants and their corresponding Google Review URLs was extracted using the Octoparse data extraction tool. The tool's "Google Maps Listings Scraper" template was used, with the keyword "Restaurants in [insert zip code]" to target specific areas. This data provides the core restaurant information for the analysis, including names, ratings, and review counts.
- **Restaurant Reviews:** Google reviews for each restaurant were collected using the Octoparse data extraction tool's "Google Reviews Scraper" template. This involved inputting the previously collected Google Review URLs to extract individual reviews and their associated ratings. Review data provides valuable insights into customer

sentiment, preferences, and experiences, allowing for a deeper understanding of restaurant performance and areas for improvement.

Below are the steps for data collection:

1) Retrieving a list of San Diego **Zip Codes** with their neighborhood names via **webscraping** BkylnDesigns.com using **Python library BeautifulSoup** at the url: www.bklyndesigns.com/san-diego-zip-codes/

```
# List of San Diego Zipcodes with Their Neighborhood Names

# Install necessary libraries and packages
!pip install pandas requests beautifulsoup4

import pandas as pd
import requests
from bs4 import BeautifulSoup

# URL of the webpage
url = "https://bklyndesigns.com/san-diego-zip-codes/"

# Send a GET request to the webpage
response = requests.get(url)

# Check if the request was successful
if response.status_code == 200:
    # Parse the webpage content
    soup = BeautifulSoup(response.content, 'html.parser')

    # Find the table on the webpage
    table = soup.find('table')

    # Extract the rows from the table
    rows = table.find_all('tr')

    # Initialize a list to store the data
    data = []

    # Loop through the rows and extract ZIP code and address
    for row in rows[1:]:  # Skip the header row
        cols = row.find_all('td')
        if len(cols) >= 2:  # Ensure there are enough columns
            zip_code = cols[0].text.strip()
            address = cols[1].text.strip()
            data.append({'ZIP Code': zip_code, 'Address': address})

# Create a Data Frame from the extracted data
    df_zip = pd.DataFrame(data)
# Save Data Frame as a CSV file
    df_zip.to_csv('sd_neighborhoods.csv', index=False)

else:
    print(f"Failed to retrieve the webpage. Status code: {response.status_code}")
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (2.2.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (2.32.3)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/dist-packages (4.12.3)
Requirement already satisfied: numpy>=1.22.4 in /usr/local/lib/python3.10/dist-packages (from pandas) (1
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from p
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (20
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas) (
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests) (
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from reque
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from reque
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-packages (from beautifuls
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil
```

```
# Preview data set
df_zip.head(10)
```

	ZIP Code	Address
0	92101	Downtown, San Diego
1	92102	San Diego
2	92103	Hillcrest
3	92104	North Park
4	92105	City Heights
5	92106	Point Loma
6	92107	Ocean Beach
7	92108	Mission Valley
8	92109	Pacific Beach
9	92110	Old Town

2) Retrieving **land area information** of each San Diego zip code via **Webscraping** USA.com. Each zip code used for this code was obtained from the previous file created called "sd_neighborhoods.csv."

```
import re

# List of San Diego ZIP codes
zip_codes = ["91942", "92037", "92101", "92102", "92103", "92104", "92105", "92106",
              "92107", "92108", "92109", "92110", "92111", "92113", "92114", "92115",
              "92116", "92117", "92119", "92120", "92121", "92122", "92123", "92124",
              "92126", "92127", "92128", "92129", "92130", "92131", "92142", "92150",
              "92153"]
# Base URL
base_url = "http://www.usa.com/"

# List to store results
results = []

# Function to get land area
def get_land_area(zip_code):
    url = f"{base_url}{zip_code}-ca.htm"
    response = requests.get(url)

    if response.status_code == 200:
        soup = BeautifulSoup(response.text, 'html.parser')
        # Look for all tables
        tables = soup.find_all('table')

        for table in tables:
            for row in table.find_all('tr'):
                cells = row.find_all('td')

                # Ensure there are enough cells
                if len(cells) >= 2:
                    label = cells[0].text.strip().lower()  # Convert label to lowercase
                    value = cells[1].text.strip()  # Get the corresponding value

                    # Check for "land area"
                    if 'land area' in label:
                        # Extract just the numeric part
                        land_area_value = re.search(r'(\d+\.?\d*)\s*sq mi', value)
                        if land_area_value:
                            return land_area_value.group(1) + " sq mi"

        print(f"'Land Area' not found in tables for ZIP Code: {zip_code}")
        return None
    else:
        print(f"Failed to retrieve data for ZIP Code: {zip_code}, Status Code: {response.status_code}")
        return None

# Loop through each ZIP code and collect the results
for zip_code in zip_codes:
    land_area = get_land_area(zip_code)
    results.append({"ZIP Code": zip_code, "Land Area": land_area})

# Create a DataFrame from the results
df_land_area = pd.DataFrame(results)

# Save as CSV file
df_land_area.to_csv('sd_land_area.csv', index=False)

# Preview data
df_land_area.head(50)
```

```
'Land Area' not found in tables for ZIP Code: 92142
'Land Area' not found in tables for ZIP Code: 92150
'Land Area' not found in tables for ZIP Code: 92153
```

	ZIP Code	Land Area
0	91942	5.84 sq mi
1	92037	13.08 sq mi
2	92101	4.72 sq mi
3	92102	4.63 sq mi
4	92103	3.77 sq mi
5	92104	3.79 sq mi
6	92105	5.57 sq mi
7	92106	5.64 sq mi
8	92107	3.15 sq mi
9	92108	4.28 sq mi
10	92109	7.60 sq mi
11	92110	4.85 sq mi
12	92111	8.46 sq mi
13	92113	5.27 sq mi
14	92114	8.24 sq mi
15	92115	6.50 sq mi
16	92116	3.47 sq mi
17	92117	8.79 sq mi
18	92119	6.85 sq mi
19	92120	6.66 sq mi
20	92121	12.25 sq mi
21	92122	15.93 sq mi
22	92123	8.17 sq mi
23	92124	10.48 sq mi
24	92126	12.67 sq mi
25	92127	22.06 sq mi
26	92128	11.17 sq mi
27	92129	14.07 sq mi
28	92130	18.44 sq mi
29	92131	25.11 sq mi
30	92142	None
31	92150	None
32	92153	None

3) Retrieving **demographic information** for each zip code related to population, number of households, median income, and average income via Point2Homes.com through the url: https://www.point2homes.com/US/Neighborhood/CA/San-Diego-Demographics.html#MedianIncomeByZipcode

Because the Point2Homes.com website does not permit Webscraping, I collected the demographic data for each zip code through copy and pasting the table containing the information in an Excel spreadsheet. The file with this information (sd_demographics.xlsx) can be downloaded in the Github folder for this project and can be viewed in a Python environment using the code below.

```
# Downloading demographics data for each San Diego zipcode
df_demographics = pd.read_excel('/content/sd_demographics.xlsx')

# Viewing a preview of the downloaded data
df_demographics.head()

# Changing column "ZipCode" to "Zip Code"
df_demographics = df_demographics.rename(columns={'ZipCode': 'Zip Code'})

# Previewing data
df_demographics.head()
```

	Zip Code	Population	Number of Households	Median Income	Average Income
0	92101	46025	27295	86403	121867
1	92102	40051	14482	68900	85567
2	92103	34296	18834	94210	136652
3	92104	46613	22454	86291	106742
4	92105	72688	22847	58924	77386

4) List of restaurants and their Google Review urls were retrieved using **Octosparse data extraction tool** and the template called "Google Maps Listings Scraper (By Keyword)." For the keyword, I typed in "Restaurants in [insert zip code]." The file containing this list (sd_restaurant_listings.xlsx) can be downloaded from the Github folder of this project and can be viewed in a Python environment using the code below:

```
# Downloading demographics data for each San Diego zipcode
df_restaurant_listings = pd.read_excel('/content/sd_restaurant_listings.xlsx')

# Renaming the column for restaurant names in df_restaurant_listings
df_restaurant_listings = df_restaurant_listings.rename(columns={'Name': 'Restaurant Name'})

# Getting a list of all columns except "Zip Code"
cols = [col for col in df_restaurant_listings.columns if col != 'Zip Code']

# Appending "Zip Code" to the end of the list
cols.append('Zip Code')

# Reordering the DataFrame columns using the new list
df_restaurant_listings = df_restaurant_listings[cols]

# Viewing a preview of the downloaded data
df_restaurant_listings.head()
```

	Restaurant Name	Restaurant Rating	Review_count	Price_range	Category	Address	Tags	
0	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...	
1	Living Room Cafe & Bistro	3.0	882	$10–20	Mexican	2541 San Diego Ave	Dine-in\n·\nTakeout\n·\nDelivery	h
2	McDonald's	3.1	1,524	$1–10	Fast Food	4260 Nobel Dr	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	ht
3	Jack in the Box	3.5	2,417	$10–20	Fast Food	1110 C St	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	
4	McDonald's	3.5	1,269	$1–10	Fast Food	8929 Clairemont Mesa Blvd	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	ht

5) List of reviews of each restaurant was retrieved using Octospare data extraction tool and the template called "Google Reviews Scraper." Each url from the previous "sd_restaurant_listings.xlsx" file was inputted into the template in order to obtain reviews from each restaurant on the list. The file containing the reviews (sd_restaurant_reviews.xlsx) can be downloaded from the Github folder of this project and can be viewed in a Python environment using the code below:

```
df_reviews = pd.read_excel('/content/sd_restaurant_reviews.xlsx')

# Renaming the restaurant name column in df_reviews
df_reviews = df_reviews.rename(columns={'Name': 'Restaurant Name'})

# Viewing preview of data
df_reviews.head()
```

	Restaurant Name	Category	Restaurant Rating	Rating_count	Address	Reviewer	Re
0	100's seafood grill buffet	Buffet restaurant	5 stars	3,675	2828 Camino del Rio S, San Diego, CA 92108	Richie K	https://www.google.com/maps/contrib/1
1	100's seafood grill buffet	Buffet restaurant	5 stars	3,675	2828 Camino del Rio S, San Diego, CA 92108	Liz Rodriguez	https://www.google.com/maps/contrib/1
2	100's seafood grill buffet	Buffet restaurant	3 stars	3,675	2828 Camino del Rio S, San Diego, CA 92108	Jess D	https://www.google.com/maps/contrib/1
3	100's seafood grill buffet	Buffet restaurant	5 stars	3,675	2828 Camino del Rio S, San Diego, CA 92108	Shayok	https://www.google.com/maps/contrib/1
4	100's seafood grill buffet	Buffet restaurant	3 stars	3,675	2828 Camino del Rio S, San Diego, CA 92108	Tim A	https://www.google.com/maps/contrib/1

Data Cleaning & Preparation

The main goal of this portion is to create one clean and organized data containing information related to San Diego restaurants and their reviews. The desired dataset will contain columns with the following information:

- Restaurant name
- Zip code of each restaurant
- Population of each zip code
- Number of households per zip code
- Overall Google rating per restaurant
- Total number of Google reviews per restaurant
- Cuisine category
- Lowest menu price

- Highest menu price
- Rating for each restaurant review
- Restaurant review
- Number of Google user likes per review

Throughout the data cleaning/preparation step, I will be performing EDA to see what values are missing, which rows need to be removed, and what values need to be changed or fixed.

1) **Merging** the collected data to get one final "sd_reviews" dataset which will need to be cleaned.

```
# Combining the df_zip and df_land_area data frames by merging based on the 'Zip Code' column
zip_land_area_df = pd.merge(df_zip, df_land_area, on='ZIP Code', how='left')

# Displaying the merged DataFrame
zip_land_area_df.head(50)
```

	ZIP Code	Address	Land Area
0	92101	Downtown, San Diego	4.72 sq mi
1	92102	San Diego	4.63 sq mi
2	92103	Hillcrest	3.77 sq mi
3	92104	North Park	3.79 sq mi
4	92105	City Heights	5.57 sq mi
5	92106	Point Loma	5.64 sq mi
6	92107	Ocean Beach	3.15 sq mi
7	92108	Mission Valley	4.28 sq mi
8	92109	Pacific Beach	7.60 sq mi
9	92110	Old Town	4.85 sq mi
10	92111	Linda Vista	8.46 sq mi
11	92112	Downtown P.O. Box	NaN
12	92113	Logan Heights	5.27 sq mi
13	92114	Encanto	8.24 sq mi
14	92115	College Grove	6.50 sq mi
15	92116	Normal Heights	3.47 sq mi
16	92117	Clairemont	8.79 sq mi
17	92118	Coronado	NaN
18	92119	Navajo	6.85 sq mi
19	92120	Grantville	6.66 sq mi
20	92121	Sorrento Valley	12.25 sq mi
21	92122	University	15.93 sq mi
22	92123	Serra Mesa	8.17 sq mi
23	92124	Tierrasanta	10.48 sq mi
24	92126	Mira Mesa	12.67 sq mi
25	92127	Rancho Bernardo	22.06 sq mi
26	92128	Rancho Bernardo	11.17 sq mi
27	92129	Rancho Penasquitos	14.07 sq mi
28	92130	Carmel Valley	18.44 sq mi
29	92131	Scripps Ranch	25.11 sq mi
30	92132	Naval Supply Center	NaN
31	92134	Naval Hospital	NaN
32	92135	San Diego P.O. Box	NaN
33	92136	32nd St. Naval Station	NaN
34	92137	Midway P.O. Box	NaN

35	92138	Midway P.O. Box	NaN
36	92139	Paradise Hills	NaN
37	92140	San Diego	NaN
38	92142	Tierrasanta P.O. Box	None
39	92143	San Ysidro P.O. Box	NaN
40	92145	Miramar Air Station	NaN
41	92147	ASW Training Center	NaN
42	92149	Paradise Hills P.O. Box	NaN
43	92150	Downtown P.O. Box	None
44	92152	Spawars System Center	NaN
45	92153	Nestor P.O. Box	None
46	92154	Otay Mesa	NaN
47	92155	Naval Amphibious Base	NaN
48	92158	County Jail	NaN
49	92159	Navajo P.O. Box	NaN

```
# Converting 'ZIP Code' in zip_land_area_df to int64 to match the type of 'Zip Code' in df_demographics
zip_land_area_df['ZIP Code'] = pd.to_numeric(zip_land_area_df['ZIP Code'], errors='coerce').astype('Int64')

# Merging the data
zip_demographics_df = pd.merge(zip_land_area_df, df_demographics, left_on='ZIP Code', right_on='Zip Code', h

# Displaying the merged DataFrame
zip_demographics_df.head()
```

	ZIP Code	Address	Land Area	Zip Code	Population	Number of Households	Median Income	Average Income
0	92101	Downtown, San Diego	4.72 sq mi	92101.0	46025.0	27295.0	86403.0	121867.0
1	92102	San Diego	4.63 sq mi	92102.0	40051.0	14482.0	68900.0	85567.0
2	92103	Hillcrest	3.77 sq mi	92103.0	34296.0	18834.0	94210.0	136652.0
3	92104	North Park	3.79 sq mi	92104.0	46613.0	22454.0	86291.0	106742.0
4	92105	City Heights	5.57 sq mi	92105.0	72688.0	22847.0	58924.0	77386.0

```
# Combining df_restaurant listings and the previous zip_demographics data frame
restaurant_demographics_df = pd.merge(df_restaurant_listings, zip_demographics_df, left_on='Zip Code', right

# Displaying the merged data frame
restaurant_demographics_df.head()

# Moving "ZIP Code" to the end of restaurant_demographics_df
# Changing 'Zip Code' to 'ZIP Code' to match the actual column name
```

```
cols = [col for col in restaurant_demographics_df.columns if col != 'ZIP Code']
cols.append('ZIP Code')  # Add 'ZIP Code' to the end
restaurant_demographics_df = restaurant_demographics_df[cols]  # Reorder columns

# Displaying the updated data frame
restaurant_demographics_df.head()
```

	Restaurant Name	Restaurant Rating	Review_count	Price_range	Category	Address_x	Tags	
0	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...	
1	Living Room Cafe & Bistro	3.0	882	$10–20	Mexican	2541 San	Dine-in\n·\nTakeout\n·\nDelivery	h
2	McDonald's	3.1	1,524	$1–10	Fast Food	4260 Nobel Dr	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	ht
3	Jack in the Box	3.5	2,417	$10–20	Fast Food	1110 C St	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	
4	McDonald's	3.5	1,269	$1–10	Fast Food	8929 Clairemont Mesa Blvd	Dine-in\n·\nDrive-through\n·\nNo-contact deliv...	ht

```
# Combining the previous restaurant_demographics dataframe with df_reviews data frame for the final merge
# Combining restaurant_demographics_df with df_reviews
sd_reviews = pd.merge(restaurant_demographics_df, df_reviews, on='Restaurant Name', how='left')

# Displaying the merged data frame
sd_reviews.head()
```

	Restaurant Name	Restaurant Rating_x	Review_count	Price_range	Category_x	Address_x	Tags
0	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...
1	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...
2	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...
3	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...
4	Taco Bell	3.0	1,017	$10–20	Fast Food	9821 Aero Dr	Dine-in\n·\nDrive-through\n·\nDelivery\n \nORD...

5 rows × 27 columns

2) Remove unnecessary columns: Address_x, Tags, Detail_URL, Category_y, Rating_count, Address, Reviewer, Reviewer_page, Review_time, Store_reply, Zip Code_y, ZIP Code

```
# Specifying the columns to remove
columns_to_remove = ['Address_x', 'Tags', 'Detail_URL', 'Category_y', 'Rating_count', 'Address', 'Reviewer',

# Removing columns using drop() method
sd_reviews = sd_reviews.drop(columns=columns_to_remove)

# Previewing data
sd_reviews.head()
```

	Restaurant Name	Restaurant Rating_x	Review_count	Price_range	Category_x	Zip Code_x	Address_y	Land Area	Population	H
0	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None	NaN	
1	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None	NaN	
2	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None	NaN	
3	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None	NaN	
4	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None	NaN	

3) Changing the names of the columns to make them code-friendly:

```
# Changing names of columns
# Creating a dictionary mapping old column names to new column names
new_column_names = {
    "Restaurant Name": "restaurant_name",
    "Restaurant Rating_x": "rating",
    "Review_count": "review_count",
    "Category_x": "cuisine_type",
    "Zip Code_x": "zip_code",
    "Address_y": "neighborhood",
    "Land Area": "land_area",
    "Population": "population",
    "Number of Households": "num_households",
    "Median Income": "median_income",
    "Average Income": "average_income",
    "Restaurant Rating_y": "review_rating",
    "Review": "review",
    "Likes": "review_likes"
}

# Renaming columns using rename() method
sd_reviews = sd_reviews.rename(columns=new_column_names)
```

```
# Previewing data
sd_reviews.head()
```

	restaurant_name	rating	review_count	Price_range	cuisine_type	zip_code	neighborhood	land_area
0	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None
1	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None
2	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None
3	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None
4	Taco Bell	3.0	1,017	$10–20	Fast Food	92142	Tierrasanta P.O. Box	None

4) Create two columns from "Price_range" column: one called "lowest_price" and the other called "highest_price." These prices will represent the lowest and highest menu prices for each restaurant.

```
# Removing all dollar signs from the column's values
sd_reviews['Price_range'] = sd_reviews['Price_range'].astype(str).str.replace('$', '', regex=False)

# Removing all rows where value for "Price_range" column is "nan" or blank
sd_reviews = sd_reviews[sd_reviews["Price_range"] != ""]
sd_reviews = sd_reviews[sd_reviews["Price_range"] != "nan"]

# Custom function to split price range
def split_price_range(price_range):
    """Splits the price range string into lowest and highest prices.

    Args:
        price_range (str): The price range string (e.g., "10-20", "30", "100+").

    Returns:
        tuple: A tuple containing the lowest and highest prices as floats,
               or (float, pd.NA) if only one price is provided,
                or (float, inf) if the price is "100+".
    """
    # Replacing en-dash with hyphen before splitting
    # Checking if price_range is a string before applying replace
    if isinstance(price_range, str):
        price_range = price_range.replace('–', '-')

        # Handle "100+" case
        if price_range.endswith('+'):
            try:
                return float(price_range[:-1]), float('inf') # Use infinity for highest
            except ValueError:
                return pd.NA, pd.NA

        prices = price_range.split('-')
        if len(prices) == 2:
            try:
                return float(prices[0]), float(prices[1])  # Convert to floats
            except ValueError:
                return pd.NA, pd.NA
        elif len(prices) == 1:
            try:
                return float(prices[0]), pd.NA  # Single price, highest is NA
            except ValueError:
                return pd.NA, pd.NA
        else:
            return pd.NA, pd.NA  # Invalid format, both are NA
    else:
        return pd.NA, pd.NA # Handle non-string values


# Applying the function and assign to new columns
sd_reviews[['lowest_price', 'highest_price']] = sd_reviews['Price_range'].apply(lambda x: pd.Series(split_pr

# Getting the current index of "Price_range"
price_range_index = sd_reviews.columns.get_loc('Price_range')

# Removing "Price_range" column
sd_reviews = sd_reviews.drop(columns=['Price_range'])

# Inserting "lowest_price" and "highest_price" at the previous index of "Price_range"
sd_reviews.insert(price_range_index, 'lowest_price', sd_reviews.pop('lowest_price'))
sd_reviews.insert(price_range_index + 1, 'highest_price', sd_reviews.pop('highest_price'))

# Previewing data
sd_reviews.head()
```

	restaurant_name	rating	review_count	lowest_price	highest_price	cuisine_type	zip_code	neighborh
0	Taco Bell	3.0	1,017	10.0	20.0	Fast Food	92142	Tierrasa P.O.
1	Taco Bell	3.0	1,017	10.0	20.0	Fast Food	92142	Tierrasa P.O.
2	Taco Bell	3.0	1,017	10.0	20.0	Fast Food	92142	Tierrasa P.O.
3	Taco Bell	3.0	1,017	10.0	20.0	Fast Food	92142	Tierrasa P.O.
4	Taco Bell	3.0	1,017	10.0	20.0	Fast Food	92142	Tierrasa P.O.

5) Right away, I can see that the first several rows of data do not have values for "land_area," "population," "num_households," "median_income," and "average_income." These are going to be important indicators later one, so I will be removing rows that do not have these values.

```
# Removing rows with empty values for land_area, population, num_households, median_income, and average_inco
sd_reviews = sd_reviews.dropna(subset=['land_area', 'population', 'num_households', 'median_income', 'averag

# Previewing data
sd_reviews.head()
```

	restaurant_name	rating	review_count	lowest_price	highest_price	cuisine_type	zip_code	neighbo
501	Living Room Cafe & Bistro	3.0	882	10.0	20.0	Mexican	92110	Olc
502	Living Room Cafe & Bistro	3.0	882	10.0	20.0	Mexican	92110	Olc
503	Living Room Cafe & Bistro	3.0	882	10.0	20.0	Mexican	92110	Olc
504	Living Room Cafe & Bistro	3.0	882	10.0	20.0	Mexican	92110	Olc
505	Living Room Cafe & Bistro	3.0	882	10.0	20.0	Mexican	92110	Olc

6) Now that most of the data has been cleaned up, I will be performing some minor EDA to see if there is anything help that needs to be improved. I will start by getting a summary of the overall data, then will examine the details of the data in each categorical column.

```
# Summary of data
sd_reviews.info(0)

# Number of missing values per column
sd_reviews.isnull().sum()

# Categorical columns to observe
categorical_cols = ['restaurant_name', 'cuisine_type', 'neighborhood']

# Printing unique values and their counts for each column
for column in categorical_cols:
    print(f"Unique values for '{column}':")
    unique_values = sd_reviews[column].unique()
    num_unique = len(unique_values)  # Get the number of unique values
    print(f"Number of unique values: {num_unique}")
    for value in unique_values:
        print(value)
    print("\n")  # Add a separator between columns
```

```
Colombian
Japanese Curry
Fine Dining
Irish pub
Shawarma restaurant
Deli
Lounge
Gay bar
Cuban
Vegan
Spanish
Noodle Shop
French
Vegetarian
Izakaya
Ethiopian
Dessert shop
Hot Dog
Georgian
Venezuelan
Latin American
Lebanese
Pastries
Hawaiian
Taiwanese


Unique values for 'neighborhood':
Number of unique values: 27
Old Town
University
San Diego
Serra Mesa
Mira Mesa
Hillcrest
Navajo
Mission Valley
Rancho Penasquitos
Scripps Ranch
Tierrasanta
Sorrento Valley
City Heights
North Park
Logan Heights
Clairemont
Downtown, San Diego
Encanto
Point Loma
Grantville
College Grove
Pacific Beach
Rancho Bernardo
Carmel Valley
Linda Vista
Ocean Beach
Normal Heights
```

7) Immediately, I notice that column "review_likes" has 33,126 missing values. This shows that it is not common for people to like other users' Google reviews or that "likes" do not occur very frequently. This column will be insignificant for my analysis, so I will remove it altogether. I will also remove rows with missing values for the "review" and "review_rating" columns.

```
# Removing "review_likes" column
sd_reviews = sd_reviews.drop(columns=['review_likes'])

# Removing rows with missing values in "review" and "review_rating"
sd_reviews = sd_reviews.dropna(subset=['review', 'review_rating'])

# Performing EDA again for all categorical variable columns
categorical_cols = ['restaurant_name', 'cuisine_type', 'neighborhood']

# Printing unique values and their counts for each column
for column in categorical_cols:
    print(f"Unique values for '{column}':")
    unique_values = sd_reviews[column].unique()
    num_unique = len(unique_values)  # Get the number of unique values
    print(f"Number of unique values: {num_unique}")
    for value in unique_values:
        print(value)
    print("\n")  # Add a separator between columns
```

```
Unique values for 'restaurant_name':
Number of unique values: 623
Living Room Cafe & Bistro
McDonald's
Jack in the Box
Pizza Hut
Paradise Biryani Pointe
Hong Kong Restaurant
Buffalo Wild Wings
Chipotle Mexican Grill
Rasraj San Diego
Pho Ca Dao Vietnamese Kitchen
Popeyes Louisiana Kitchen
Primos Mexican Food & Cantina
Taco Bell
Punjabi Tandoor
Panda Express
Saguaro's Mexican Food
Pho La Jolla
Sunrise Buffet
Rally's
Seaside Buffet
Royal India - San Diego
GOLDEN ISLAND - Dim Sum & Chinese Cuisine
Wendy's
Panera Bread
Carl’s Jr.
El Pollo Loco
Bandar Restaurant
Los Tito's Mexican Food
Vaqueros Carne Asada
Mikami Bar & Revolving Sushi, Convoy San Diego
Claim Jumper Steakhouse & Bar - San Diego, CA
Hooters of Mission Valley
Taquería Imperial
Denny's
El Salvador Pupuseria Y Restaurante!
Vallarta Express Mexican Eatery
356 Korean BBQ & Bar
Cotixan Mexican Food
Corner Bakery Cafe
Tony's Fresh Mexican Food
Burritos Santana
```

```
Tandoori House - Indian Restaurant & Catering Services
Chuck E. Cheese
Urban India Restaurant & Bar
Cotijas Mex Grill
Bunz
Casa de Maria Restaurant
Cabo Cantina
Sammys Food & Wine
Fortunate Son Chinese
Huapangos
Great Plaza Buffet
Old Town Tequila Factory Restaurant & Cantina
Barra Barra
Chili's Grill & Bar
Broken Yolk Cafe
```

8) Looking further, I notice that there are still some more things that need to be fixed about the data. I will use this step to make any final changes to the data set. I see that "San Diego" is written as one of the neighborhoods within the city of San Diego. I will check which zip code was assigned "San Diego" as its neighborhood and will manually search for the actually name of the neighborhood. Then, I will replace "San Diego" with the actual neighborhood name for the respective zip code.

```
# Finding zip codes with neighborhood "San Diego"
san_diego_zip_codes = sd_reviews[sd_reviews['neighborhood'] == 'San Diego']['zip_code'].unique()

# Printing the results
print("Zip codes with neighborhood 'San Diego':")
for zip_code in san_diego_zip_codes:
    print(zip_code)

# Output says "92102", which belongs to Downtown San Diego. Replace all values
# under "neighborhood" that have zip code 92102 with "Downtown San Diego"

# Converting 'zip_code' column to numeric
sd_reviews['zip_code'] = pd.to_numeric(sd_reviews['zip_code'], errors='coerce')

# Replacing neighborhood values for zip code 92102
sd_reviews.loc[sd_reviews['zip_code'] == 92102, 'neighborhood'] = 'Downtown San Diego'

# Printing the results again to confirm
print("\nUpdated neighborhood values for zip code 92102:")
print(sd_reviews[sd_reviews['zip_code'] == 92102]['neighborhood'].unique())

# See all values in the "neighborhood" column to make sure they're all correct
unique_neighborhoods = sd_reviews['neighborhood'].unique()

print("Unique values in 'neighborhood' column:")
for neighborhood in unique_neighborhoods:
    print(neighborhood)

# Replacing "Downtown, San Diego" with "Downtown San Diego" using regex
sd_reviews['neighborhood'] = sd_reviews['neighborhood'].str.replace(r'Downtown,\s*San Diego', 'Downtown San

print("Unique values in 'neighborhood' column:")
for neighborhood in unique_neighborhoods:
    print(neighborhood)

# Removing "stars" from review_rating column and extract numeric rating
sd_reviews['review_rating'] = sd_reviews['review_rating'].str.extract(r'(\d+)').astype(float)
```

```
Zip codes with neighborhood 'San Diego':
92102

Updated neighborhood values for zip code 92102:
['Downtown San Diego']
Unique values in 'neighborhood' column:
Old Town
University
Downtown San Diego
Serra Mesa
Mira Mesa
Hillcrest
Navajo
Mission Valley
Rancho Penasquitos
Scripps Ranch
Tierrasanta
Sorrento Valley
City Heights
North Park
Logan Heights
Clairemont
Downtown, San Diego
Encanto
```

```
Point Loma
Grantville
College Grove
Pacific Beach
Rancho Bernardo
Carmel Valley
Linda Vista
Ocean Beach
Normal Heights
Unique values in 'neighborhood' column:
Old Town
University
Downtown San Diego
Serra Mesa
Mira Mesa
Hillcrest
Navajo
Mission Valley
Rancho Penasquitos
Scripps Ranch
Tierrasanta
Sorrento Valley
City Heights
North Park
Logan Heights
Clairemont
Downtown, San Diego
Encanto
Point Loma
Grantville
College Grove
Pacific Beach
```

```python
# There are 93 different cuisine categories.
# Consolidating the categories into broader types

# Function to categorize cuisine types
def categorize_cuisine(cuisine):
    if cuisine in ['Japanese', 'Sushi', 'Ramen', 'Noodles', 'Chinese', 'Thai', 'Korean', 'Vietnamese', 'Taiw
        return 'Asian'
    elif cuisine in ['American (Traditional)', 'Burgers', 'Sandwiches', 'Fast Food', 'Hot Dogs', 'Chicken Wi
        return 'American'
    # Updated: Added Pizza to Italian
    elif cuisine in ['Italian', 'Pizza', 'Pizza Delivery']:
        return 'Italian'
    # Updated: Added Greek to Mediterranean
    elif cuisine in ['Mediterranean', 'Greek']:
        return 'Mediterranean'
    elif cuisine in ['French']:
        return 'French'
    # Updated: Added Spanish to Latin American
    elif cuisine in ['Mexican', 'Argentinian','Latin American', 'Caribbean', 'Cuban', 'Salvadoran', 'Spanish
        return 'Latin American'
    elif cuisine in ['Portuguese']:
        return 'Portuguese'
    elif cuisine in ['Turkish']:
        return 'Turkish'
    elif cuisine in ['Middle Eastern', 'Lebanese']:
        return 'Middle Eastern'
    elif cuisine in ['Cafes', 'Coffee & Tea', 'Bakeries', 'Desserts', 'Ice Cream & Frozen Yogurt']:
        return 'Cafes & Desserts'
    elif cuisine in ['Vegetarian', 'Vegan', 'Gluten-Free', 'Healthy']:
        return 'Health-conscious'
    else:
        return 'Other'  # For any uncategorized cuisines

# Applying the categorization function
sd_reviews['cuisine_category'] = sd_reviews['cuisine_type'].apply(categorize_cuisine)

# Printing unique values in "cuisine_category"
unique_categories = sd_reviews['cuisine_category'].unique()

print("Unique Cuisine Categories:")
for category in unique_categories:
    print(category)
```

```
Unique Cuisine Categories:
Latin American
American
Italian
Asian
Other
Mediterranean
Middle Eastern
Health-conscious
French
```

```
# Giving the restaurants labeled "Other" specific categories
# Function to categorize based on restaurant name
def categorize_by_name(name):
    name_lower = name.lower() # Convert to lowercase for case-insensitive matching
    if any(keyword in name_lower for keyword in ['vietnamese', 'pho', 'banh mi', 'thai', 'chinese', 'japanes
        return 'Asian'
    elif any(keyword in name_lower for keyword in ['italian', 'pizza', 'pasta', 'trattoria', 'pizzeria']):
        return 'Italian'
    elif any(keyword in name_lower for keyword in ['mexican', 'taco', 'burrito', 'taqueria', 'cantina']):
        return 'Latin American'
    elif any(keyword in name_lower for keyword in ['burger', 'fries', 'american', 'grill', 'diner', 'bbq', '
        return 'American'
    elif any(keyword in name_lower for keyword in ['cafe', 'coffee', 'bakery', 'dessert', 'ice cream']):
        return 'Cafes & Desserts'
    elif any(keyword in name_lower for keyword in ['mediterranean', 'greek', 'gyro', 'falafel']):
        return 'Mediterranean'
    # Add more conditions as needed for other cuisines based on name patterns
    else:
        return 'Other' # If no keywords match, keep as 'Other'

# Filtering restaurants categorized as "Other"
other_restaurants = sd_reviews[sd_reviews['cuisine_category'] == 'Other']

# Applying the name-based categorization to the filtered restaurants
other_restaurants['cuisine_category'] = other_restaurants['restaurant_name'].apply(categorize_by_name)

# Updating the original DataFrame with the new categories
sd_reviews.update(other_restaurants) # Update sd_reviews with changes in other_restaurants

# Getting unique values in "cuisine_category"
unique_categories = sd_reviews['cuisine_category'].unique()

# Printing the unique values
print("Unique Cuisine Categories:")
```

```
for category in unique_categories:
    print(category)
```

```
<ipython-input-19-04492ca463d2>:25: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.h
  other_restaurants['cuisine_category'] = other_restaurants['restaurant_name'].apply(categorize_by_name)
Unique Cuisine Categories:
Latin American
American
Italian
Asian
Other
Cafes & Desserts
Mediterranean
Middle Eastern
Health-conscious
French
```

```
# Creating "population_density" column
# Removing "sq mi" and extract numeric values from 'land_area' column
sd_reviews['land_area'] = sd_reviews['land_area'].str.replace(' sq mi', '', regex=False).astype(float)

# Adding "poupulation_density" column after "population" by dividing "population" column
# by the "land_area" column
sd_reviews.insert(sd_reviews.columns.get_loc('population') + 1, 'population_density', sd_reviews['population'


# Getting data types for "review_rating" and "review_count" columns
rating_dtype = sd_reviews['review_rating'].dtype
review_count_dtype = sd_reviews['review_count'].dtype

# Printing the data types
print(f"Data type of 'review_rating': {rating_dtype}")
print(f"Data type of 'review_count': {review_count_dtype}")

# Changing "review_count" to numeric
sd_reviews['review_count'] = pd.to_numeric(sd_reviews['review_count'], errors='coerce')

# Printing dtype for review count to confirm change
print(f"Data type of 'review_count': {sd_reviews['review_count'].dtype}")

sd_reviews = sd_reviews.reset_index(drop=True) # Reset the index, removing the old one
sd_reviews.index = sd_reviews.index + 1 # Start the index from 1
```

```
Data type of 'review_rating': float64
Data type of 'review_count': object
Data type of 'review_count': float64
```

9) "sd_reviews" data set has now been cleaned. Below is a preview of the final data set.

```
# Preview of final data set
sd_reviews.head()
```

	restaurant_name	rating	review_count	lowest_price	highest_price	cuisine_type	zip_code	neighborh
1	Living Room Cafe & Bistro	3.0	882.0	10.0	20.0	Mexican	92110	Old To
2	Living Room Cafe & Bistro	3.0	882.0	10.0	20.0	Mexican	92110	Old To
3	Living Room Cafe & Bistro	3.0	882.0	10.0	20.0	Mexican	92110	Old To
4	Living Room Cafe & Bistro	3.0	882.0	10.0	20.0	Mexican	92110	Old To
5	Living Room Cafe & Bistro	3.0	882.0	10.0	20.0	Mexican	92110	Old To

Exploratory Data Analysis (EDA)

In this section, EDA will be performed on the cleaned sd_reviews data set. The purpose of performing EDA prior to building machine learning models and data visualization graphs is to gain a deeper understanding of the data itself and draw initial conclusions. This portion will involve calculating descriptive statistics, as well as observing the relationships between the variables to see what specific factors influence restaurant ratings.

1) Descriptive Statistics: this section aims to provide a basic understanding of the distribution and central tendencies of the sd_reviews data set's numerical and categorical features.

```
# Get descriptive statistics for numerical features
numerical_features = ['rating', 'review_count', 'lowest_price', 'highest_price', 'population', 'num_househol
sd_reviews[numerical_features].describe()

# Calculate descriptive statistics for numerical features grouped by cuisine category
sd_reviews.groupby('cuisine_category')[numerical_features].describe()

# Calculate descriptive statistics for numerical features grouped by neighborhood
sd_reviews.groupby('neighborhood')[numerical_features].describe()
```

```
# Get frequency counts for categorical features
categorical_features = ['cuisine_category', 'neighborhood']
for feature in categorical_features:
    print(f"Frequency counts for {feature}:")
    print(sd_reviews[feature].value_counts())
    print("\n")
```

```
Frequency counts for cuisine_category:
cuisine_category
American            21918
Other                6565
Asian                4755
Latin American       4083
Italian              2541
Mediterranean          69
Cafes & Desserts       57
Health-conscious       18
French                  8
Middle Eastern          6
Name: count, dtype: int64


Frequency counts for neighborhood:
neighborhood
Downtown San Diego    7679
Mission Valley        3990
Scripps Ranch         2805
Mira Mesa             2581
North Park            2301
Serra Mesa            2263
Tierrasanta           1919
University            1789
City Heights          1697
Logan Heights         1524
Point Loma            1429
Pacific Beach         1305
Rancho Penasquitos    1236
Old Town              1134
Linda Vista           1034
Navajo                 997
Rancho Bernardo        758
Ocean Beach            725
Hillcrest              698
Grantville             503
Clairemont             496
Sorrento Valley        401
Normal Heights         349
Carmel Valley          334
College Grove           42
Encanto                 31
Name: count, dtype: int64
```

2) Relationships between numeric vs. numeric variables and numeric vs. categorical variables:

Double-click (or enter) to edit

```
# Correlation between rating and numerical features
sd_reviews[['rating', 'population_density', 'median_income', 'average_income', 'review_count', 'lowest_price
```

	rating	population_density	median_income	average_income	review_count	lowest_pric
rating	1.000000	0.228075	-0.056121	0.015239	-0.104018	0.36013
population_density	0.228075	1.000000	-0.772179	-0.716530	0.166396	0.22415
median_income	-0.056121	-0.772179	1.000000	0.968162	-0.339819	-0.17620
average_income	0.015239	-0.716530	0.968162	1.000000	-0.346085	-0.10158
review_count	-0.104018	0.166396	-0.339819	-0.346085	1.000000	0.13689
lowest_price	0.360135	0.224158	-0.176207	-0.101580	0.136896	1.00000
highest_price	0.382265	0.195607	-0.192600	-0.137487	0.144807	0.97917

```
# Correlation between cuisine category and restaurant rating: Average rating per category
sd_reviews.groupby('cuisine_category')['rating'].mean().sort_values(ascending=False)
```

	rating
cuisine_category	
Health-conscious	4.644444
French	4.625000
Middle Eastern	4.600000
Mediterranean	4.468116
Cafes & Desserts	4.445614
Italian	4.278749
Other	4.174760
Latin American	4.003282
American	3.976043
Asian	3.934406

```
# Relationship between neighborhood and rating: Average restaurant rating per neighborhood
sd_reviews.groupby('neighborhood')['rating'].mean().sort_values(ascending=False)
```

	rating
neighborhood	
Ocean Beach	4.553103
Normal Heights	4.512894
Rancho Bernardo	4.460950
Pacific Beach	4.426973
College Grove	4.423810
Linda Vista	4.401741
Grantville	4.368191
Encanto	4.329032
Point Loma	4.253884
Carmel Valley	4.129042
Hillcrest	4.116762
Downtown San Diego	4.114103
Mission Valley	4.093434
North Park	4.092003
Logan Heights	3.993045
Mira Mesa	3.966098
Clairemont	3.961089
Tierrasanta	3.927983
Old Town	3.903439
Serra Mesa	3.893283
City Heights	3.890100
Scripps Ranch	3.868592
Sorrento Valley	3.855112
Rancho Penasquitos	3.711974
Navajo	3.621364
University	3.440973

3) Food rating differences amongst various cuisine categories by San Diego neighborhood:

```
# Food rating differences amongst various cuisine categories in
# different San Diego neighborhoods
def print_neighborhood_food_ratings(df):

    # Calculate average ratings per food category in each neighborhood
    neighborhood_food_ratings = df.groupby(['neighborhood', 'cuisine_category'])['rating'].mean().reset_inde
    # Sort by neighborhood and rating for better readability
    neighborhood_food_ratings = neighborhood_food_ratings.sort_values(['neighborhood', 'rating'], ascending=

    # Print the results as a list
    print("\n--- Differences in Food Ratings Across Neighborhoods ---")
    for neighborhood in neighborhood_food_ratings['neighborhood'].unique():
        print(f"\nNeighborhood: {neighborhood}")
        for index, row in neighborhood_food_ratings[neighborhood_food_ratings['neighborhood'] == neighborhoc
            print(f"  {row['cuisine_category']}: {row['rating']:.2f}")

print_neighborhood_food_ratings(sd_reviews)
```

```
--- Differences in Food Ratings Across Neighborhoods ---

Neighborhood: Carmel Valley
  Asian: 4.57
  Other: 4.48
  Latin American: 4.40
  Mediterranean: 4.40
  Italian: 4.33
  American: 4.11

Neighborhood: City Heights
  Latin American: 4.39
  Other: 4.36
  Italian: 4.30
  American: 3.90
  Asian: 3.81

Neighborhood: Clairemont
  Health-conscious: 4.60
  Italian: 4.60
  Latin American: 4.47
  Cafes & Desserts: 4.40
  Middle Eastern: 4.40
  American: 4.31
  Mediterranean: 4.30
  Asian: 4.23
  Other: 3.91

Neighborhood: College Grove
  Health-conscious: 4.70
  Mediterranean: 4.60
  Italian: 4.55
  Asian: 4.43
  Cafes & Desserts: 4.40
  Latin American: 4.37
  Other: 4.35
  American: 4.20

Neighborhood: Downtown San Diego
  Other: 4.48
  Cafes & Desserts: 4.43
  Latin American: 4.40
  Mediterranean: 4.35
  Italian: 4.16
  American: 3.95
  Asian: 3.90

Neighborhood: Encanto
  Italian: 4.50
  Other: 4.40
```

```
    Asian: 4.40
    Latin American: 4.28
    American: 4.10

  Neighborhood: Grantville
    Asian: 4.50
```

4) Review count differences by cuisine category amongst various San Diego neighborhoods

```
# Review count differences amongst various San Diego neighborhoods
def print_neighborhood_review_counts(df):

    # Group by neighborhood and cuisine category and count the number of rows
    neighborhood_review_counts = df.groupby(['neighborhood', 'cuisine_category'])['restaurant_name'].count()

    # Rename the count column for clarity
    neighborhood_review_counts = neighborhood_review_counts.rename(columns={'restaurant_name': 'review_count

    # Sort by neighborhood and review count for better readability
    neighborhood_review_counts = neighborhood_review_counts.sort_values(['neighborhood', 'review_count'], as

    # Print the results as a list
    print("\n--- Number of Reviews per Food Category in Each Neighborhood ---")
    for neighborhood in neighborhood_review_counts['neighborhood'].unique():
        print(f"\nNeighborhood: {neighborhood}")
        for index, row in neighborhood_review_counts[neighborhood_review_counts['neighborhood'] == neighborh
            print(f"  {row['cuisine_category']}: {row['review_count']}")

print_neighborhood_review_counts(sd_reviews)
```

```
  --- Number of Reviews per Food Category in Each Neighborhood ---

  Neighborhood: Carmel Valley
    American: 312
    Other: 12
    Asian: 3
    Italian: 3
    Latin American: 2
    Mediterranean: 2

  Neighborhood: City Heights
    American: 1216
    Asian: 438
    Other: 25
    Latin American: 16
    Italian: 2

  Neighborhood: Clairemont
    Other: 443
    Latin American: 18
    American: 17
    Asian: 6
    Mediterranean: 4
    Cafes & Desserts: 2
    Health-conscious: 2
    Italian: 2
    Middle Eastern: 2

  Neighborhood: College Grove
    Other: 17
    Asian: 6
    Latin American: 6
    Italian: 4
    Mediterranean: 4
    Cafes & Desserts: 2
    Health-conscious: 2
    American: 1

  Neighborhood: Downtown San Diego
    American: 3624
    Italian: 1385
    Other: 1272
    Latin American: 715
    Asian: 666
    Mediterranean: 11
    Cafes & Desserts: 6

  Neighborhood: Encanto
    Latin American: 17
    Asian: 6
    Italian: 4
    American: 2
    Other: 2

  Neighborhood: Grantville
    American: 454
    Other: 25
```

Machine Learning Models & Evaluation

This section explores the application of machine learning models to address the two of the four goals of this project as previously stated in the introduction: identifying key success factors and enhancing customer experience. To achieve these goals, a variety of machine learning techniques will be leveraged to achieve each goal.

1) Random Forest Classifier Model: Identifying Key Success Factors

A Random Forest Classifier model was used to **identify key success factors** because the sd_reviews data set has a combination of categorical and numerical data. Random Forest Classifier is equipped with handling both categorical and numerical features without requiring extensive preprocessing or transformations. This model also allows one to assess feature importance, which is important for addressing key factors in a restaurant's sucess.

The Random Model Classifier below a measures the success of restaurants against a variety of features. "Success" is measured by a restaurant having an overall rating of 4-stars or more. The outputted results show the relative importance of different features in predicting restaurant success. The higher the importance score, the more influential the feature is in the model's predictions. Rating (0.861155) is the most important feature, but that is self-explanatory as the ratings reviewers leave will determine the overall rating of the restaurant. The second most import feature is review count (0.105908). This suggests that more visibility and customer engagement can be an indicator of customer success and that restaurants rated 4-stars or more tend to receive more reviews. The third and fourth most important features are the Asian (0.016447) and Italian (0.008091) cuisine categories. This indicates that restaurants which serve Asian and Italian food have a higher chance at success in San Diego than restaurants serving other types of cuisines.

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# 1. Data Preparation

# Create a target variable 'success' based on ratings (e.g., rating >= 4 is successful)
sd_reviews['success'] = (sd_reviews['rating'] >= 4).astype(int)

# Select relevant features and target variable
# Use available columns from sd_reviews
features = ['cuisine_category', 'rating', 'review_count']  # Replace with other relevant columns
target = 'success'

# One-hot encode categorical features
X = pd.get_dummies(sd_reviews[features], drop_first=True)
y = sd_reviews[target]

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 2. Model Training with Hyperparameter Tuning and Cross-Validation

# Defining parameter grid for GridSearchCV
param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [None, 5],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

# Creating and training the Random Forest Classifier with GridSearchCV
model = RandomForestClassifier(random_state=42, n_jobs=-1)
grid_search = GridSearchCV(model, param_grid, cv=3, scoring='accuracy')
grid_search.fit(X_train, y_train)

# Getting the best model from GridSearchCV
best_model = grid_search.best_estimator_

# 3. Model Evaluation

# Predicting on the test set
y_pred = best_model.predict(X_test)

# Evaluating accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy}")

# 4. Feature Importance Analysis

# Getting feature importances from the *trained* model (best_model)
feature_importances = best_model.feature_importances_ # Changed line: Use best_model instead of model

# Creating a data frame to display feature importances
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

print("\nFeature Importance:")
print(importance_df)
```

```
Model Accuracy: 1.0
```

```
Feature Importance:
                              Feature  Importance
0                              rating    0.861155
1                        review_count    0.105908
2               cuisine_category_Asian    0.016447
6             cuisine_category_Italian    0.008091
10              cuisine_category_Other    0.004074
7      cuisine_category_Latin American    0.003255
8       cuisine_category_Mediterranean    0.000499
3    cuisine_category_Cafes & Desserts    0.000429
5    cuisine_category_Health-conscious    0.000109
9      cuisine_category_Middle Eastern    0.000018
4              cuisine_category_French    0.000015
```

2) Sentiment Analysis: Enhancing Customer Experience

To understand which factors influence customer satisfaction and loyalty, sentiment analysis will be performed on the restaurant reviews in the dataset.

```
!pip install wordcloud nltk textblob
```

```
Requirement already satisfied: wordcloud in /usr/local/lib/python3.10/dist-packages (1.9.3)
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-packages (3.8.1)
Requirement already satisfied: textblob in /usr/local/lib/python3.10/dist-packages (0.17.1)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.10/dist-packages (from wordcloud)
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (from wordcloud) (10.4.
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from wordcloud) (3
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk) (1.4.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk) (2
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk) (4.66.5)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplot
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib-
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplo
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplo
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotl
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplot
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from mat
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil
```

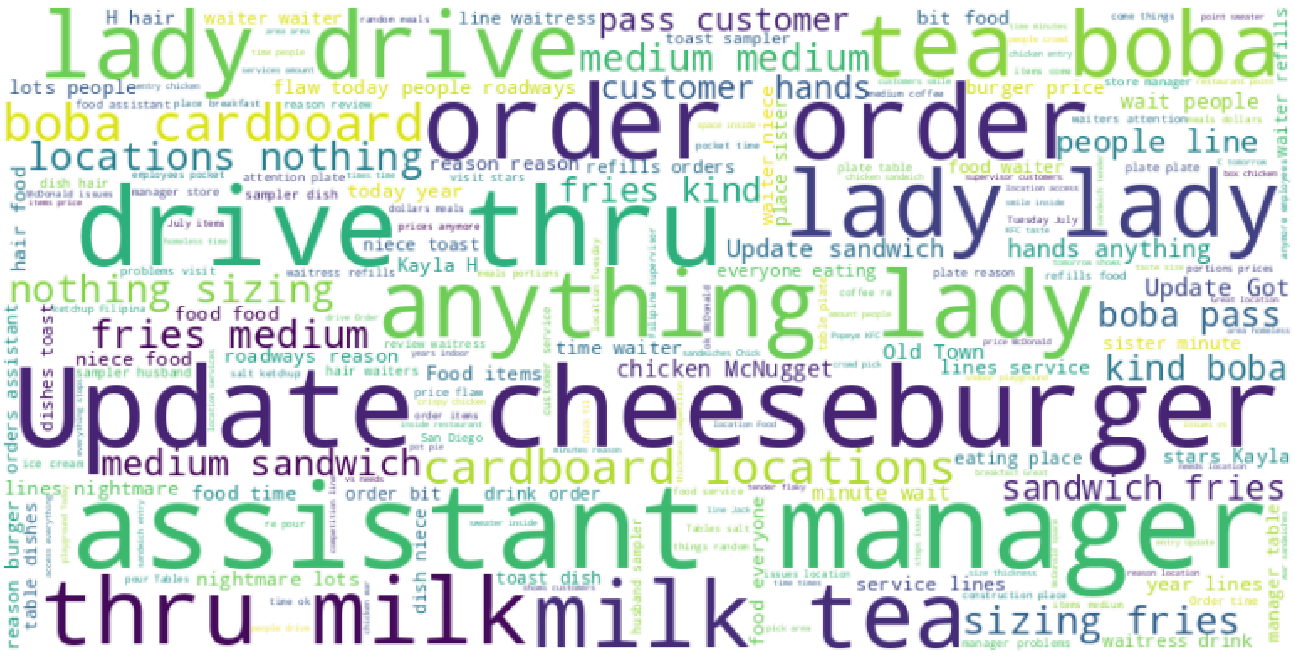
```
!python -m textblob.download_corpora
```

```
[nltk_data] Downloading package brown to /root/nltk_data...
[nltk_data]   Unzipping corpora/brown.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package conll2000 to /root/nltk_data...
[nltk_data]   Unzipping corpora/conll2000.zip.
[nltk_data] Downloading package movie_reviews to /root/nltk_data...
[nltk_data]   Unzipping corpora/movie_reviews.zip.
Finished.
```

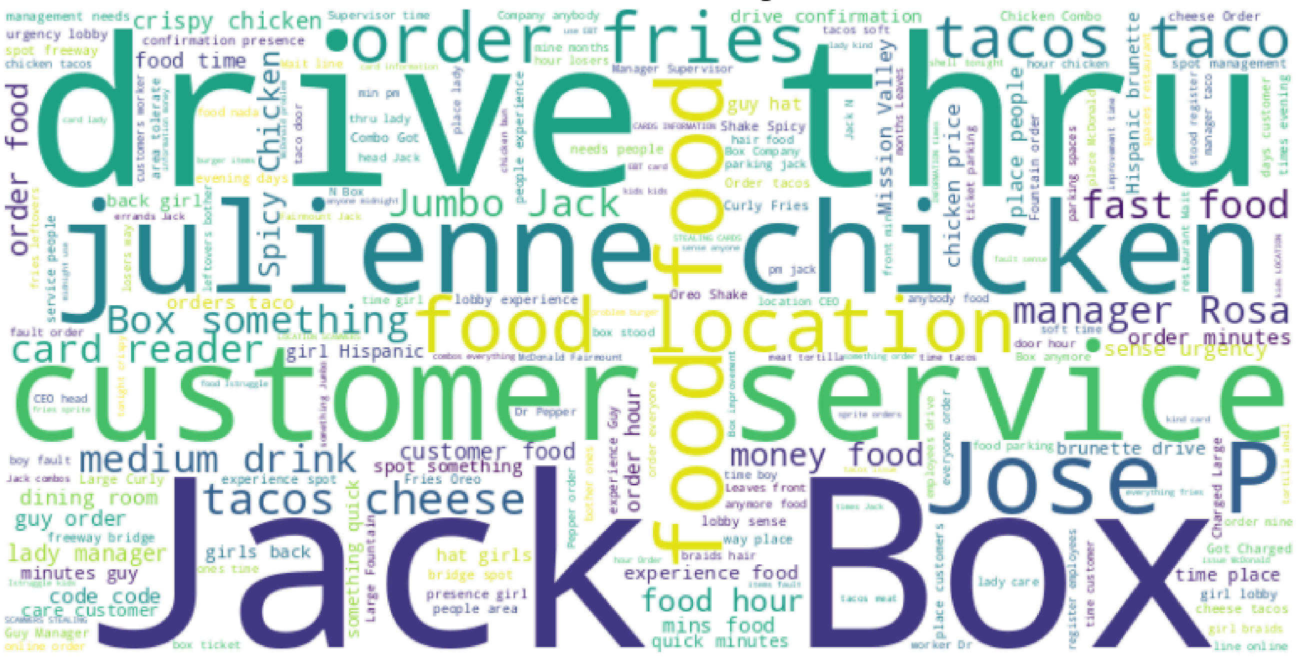
```
import pandas as pd
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from wordcloud import WordCloud
import matplotlib.pyplot as plt
from textblob import TextBlob

nltk.download('punkt')
nltk.download('stopwords')
nltk.download('vader_lexicon')

# 1. Preparing the Data
reviews_df = sd_reviews[['review', 'review_rating']].copy()

# 2. Keyword Extraction for Each Star Rating
def extract_keywords(text):
    """Extract keywords from a text using TextBlob."""
    blob = TextBlob(text)
    keywords = [word for word, tag in blob.tags if tag.startswith('NN') and word.lower() not in stopwords.wo
    return keywords

reviews_df['keywords'] = reviews_df['review'].astype(str).apply(extract_keywords)

# 3. Generating Word Clouds for Each Star Rating
star_ratings = reviews_df['review_rating'].unique()  # Changed to 'review_rating'

for rating in star_ratings:
    rating_reviews = reviews_df[reviews_df['review_rating'] == rating]  # Changed to 'review_rating'
    all_keywords = [keyword for keywords_list in rating_reviews['keywords'] for keyword in keywords_list]
    keyword_text = ' '.join(all_keywords)

    wordcloud = WordCloud(width=800, height=400, background_color='white').generate(keyword_text)

    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Word Cloud for Rating {rating}')
    plt.show()
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

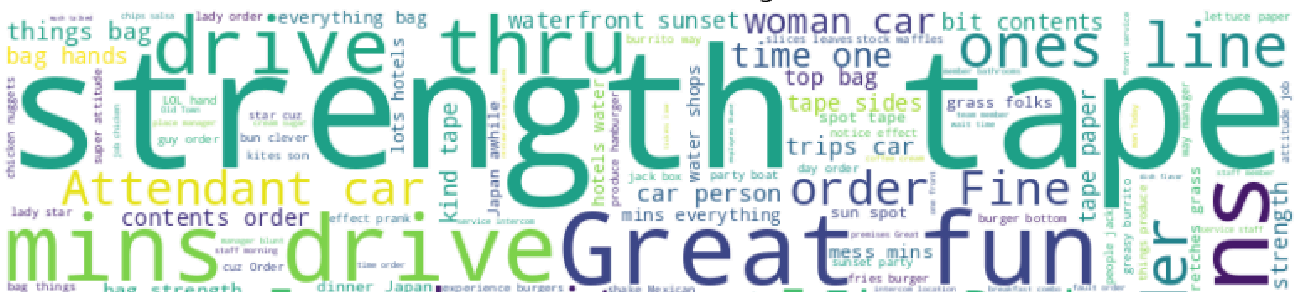
Word Cloud for Rating 3.0

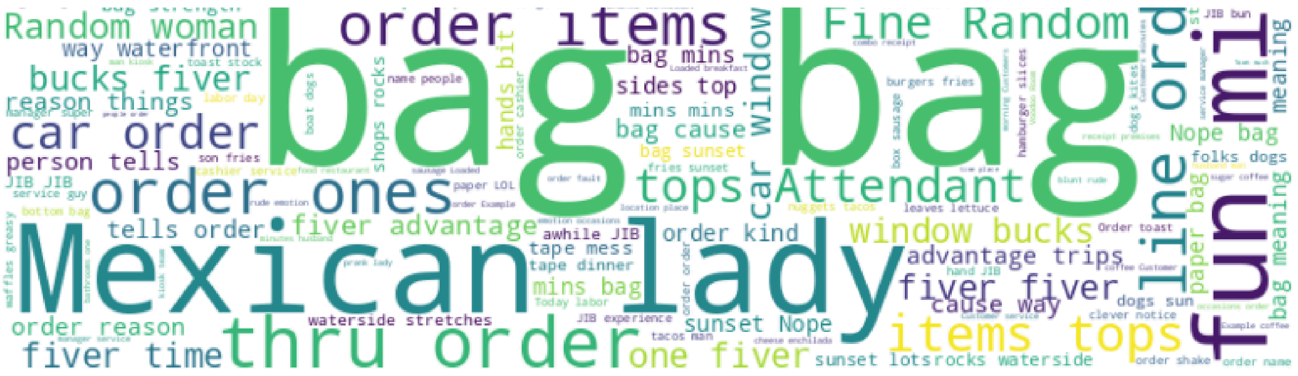


Word Cloud for Rating 1.0

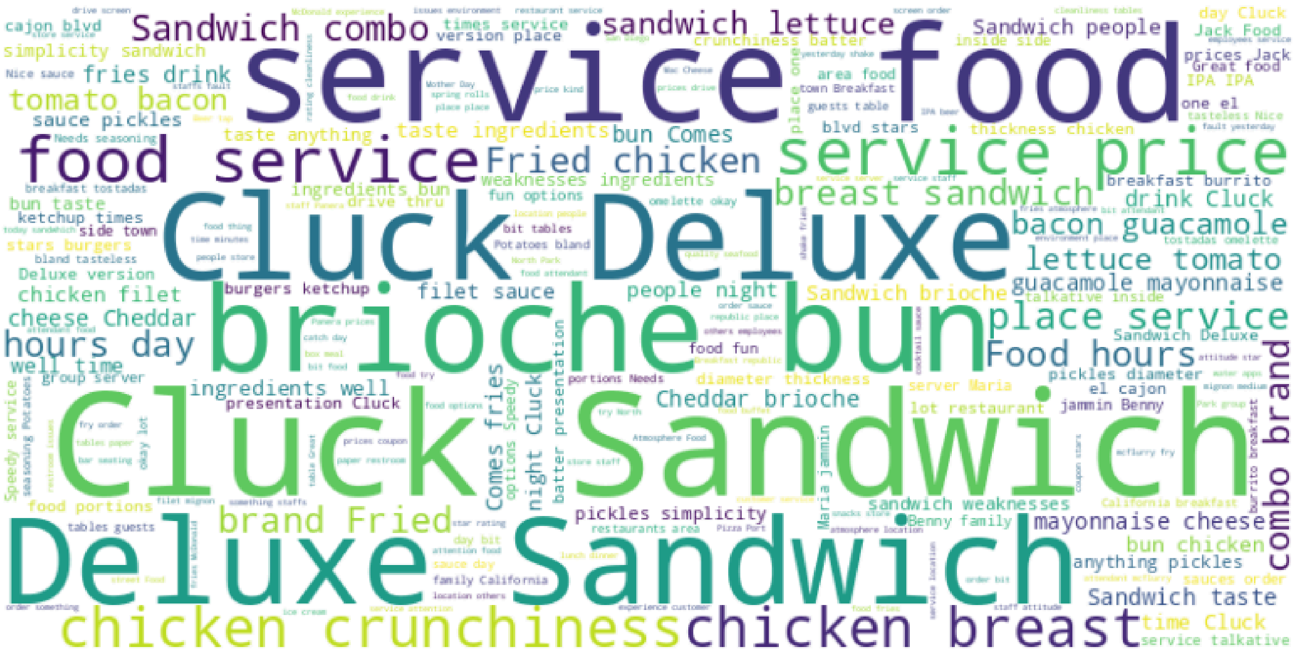


Word Cloud for Rating 2.0

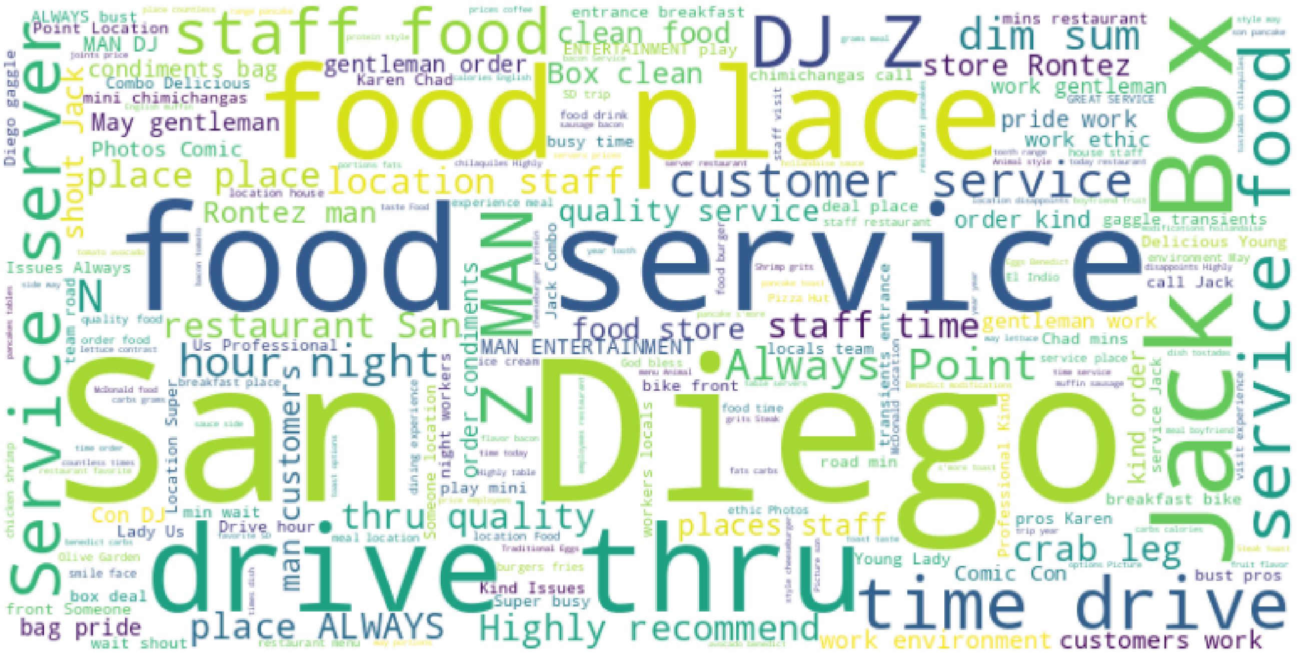




Word Cloud for Rating 4.0



Word Cloud for Rating 5.0



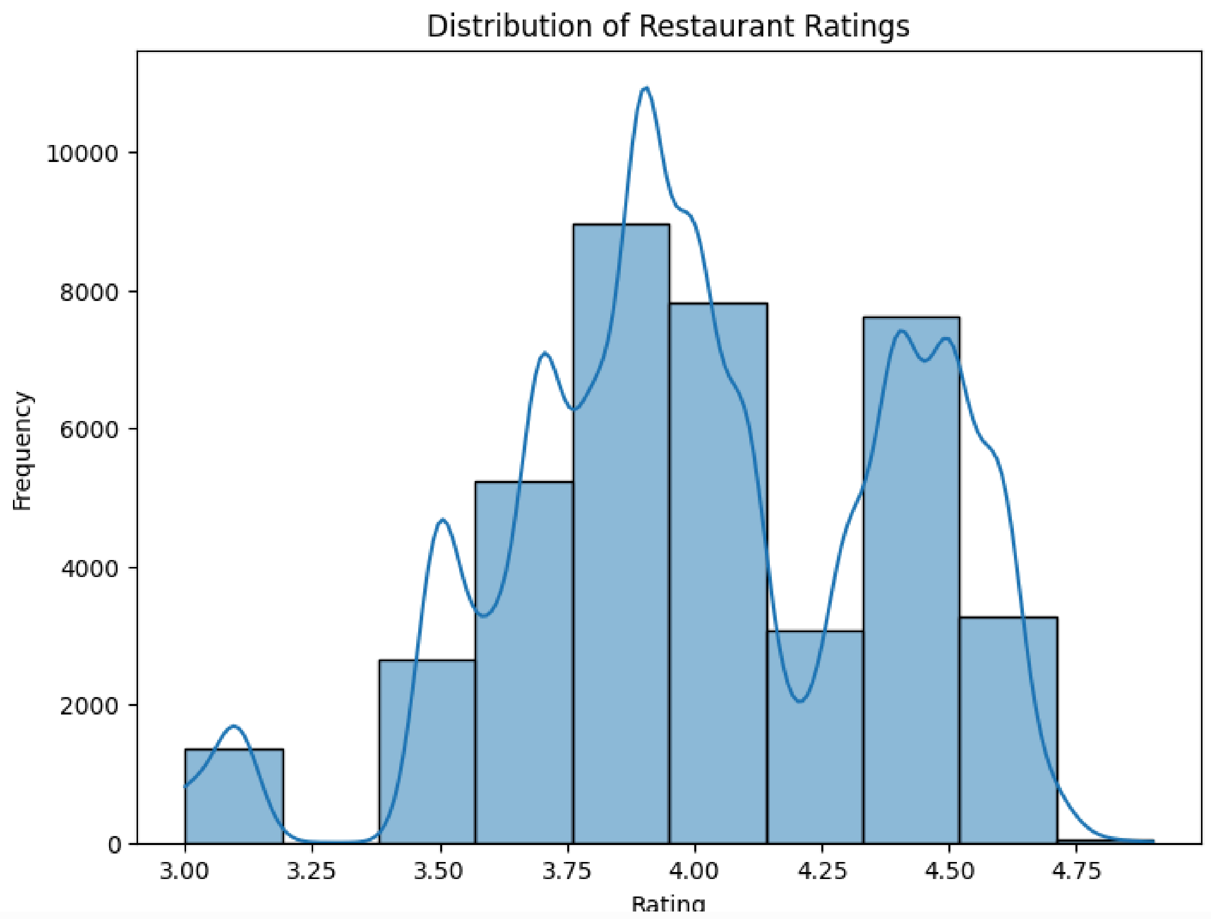
Data Visualization

This section presents various visualizations to illustrate the key findings related to restaurant success factors, optimal locations, competitive strategies, menu pricing, and customer experience in San Diego, California. These visualizations aim to provide a clear and conside overview of the patterns and trends identified in the data, allowing new and prospective restaurant owners to make informed business decisions.

```
# Importing necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns
```

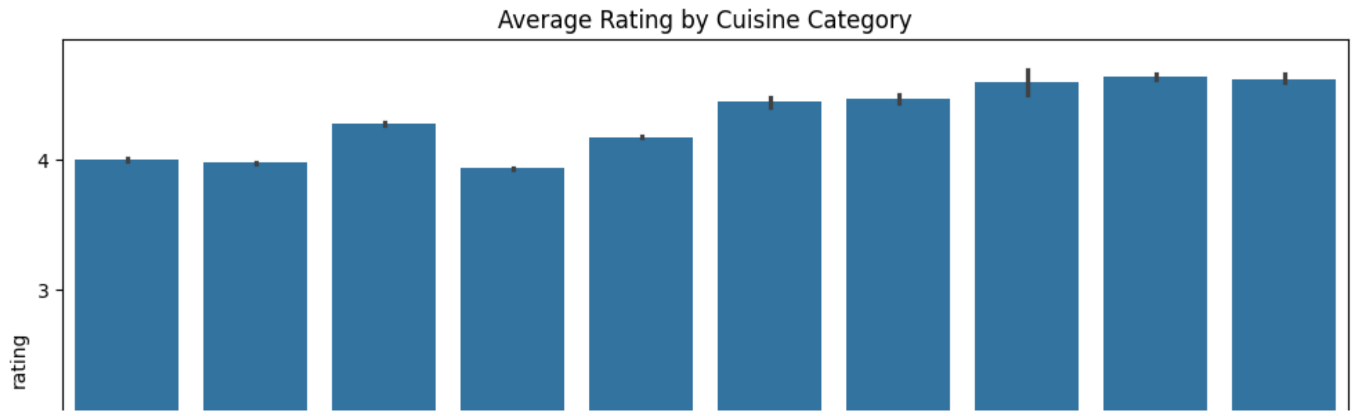
Distribution of Restaurant Ratings

```
# Distribution of Restaurant Ratings
plt.figure(figsize=(8, 6))
sns.histplot(sd_reviews['rating'], bins=10, kde=True)
plt.title('Distribution of Restaurant Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```



Average Restaurant Rating by Cuisine Category

```
# Average Rating by Cuisine Category
plt.figure(figsize=(12, 6))
sns.barplot(x='cuisine_category', y='rating', data=sd_reviews)
plt.title('Average Rating by Cuisine Category')
plt.xticks(rotation=45, ha='right')
plt.show()
```


Average Rating by Cuisine Category
rating